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USING NEURAL NETWORKS TO ASSIST IN OPAD DATA ANALYSIS

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INTRODUCTION

Plume emission spectroscopy can be applied to rocket engine testing by treating the engine plume as a precisely-controlled laboratory flame for chemical analysis. Test stand or remotely-mounted telescopes can collect engine plume emissions and direct the light, via a grating spectrometer system, onto a linear array of silicon photodetectors. In a quantitative manner, light from many wavelengths of interest can be compared to identify elements, ratioed to recognize alloys, or monitored as a function of time to establish trends and the onset of significant material erosion.

The space shuttle main engine (SSME) became the subject of plume emission spectroscopy in 1986 when researchers from NASA-Marshall Space Flight Center (MSFC), Arnold Engineering Development Center (AEDC), and Rocketdyne went to the SSME test stands at the NASA-Stennis Space Center and at Rocketdyne's Santa Susana Field Laboratory to optically observe the plume. Since then, plume spectral acquisitions have recorded many nominal tests and the qualitative spectral features of the SSME plume are now well established. Significant discoveries made with both wide-band and narrow-band plume emission spectroscopy systems led MSFC to promote the Optical Plume Anomaly Detection (OPAD) program with a goal of instrumenting all SSME test stands with customized spectrometer systems.

A prototype OPAD system is now installed on the SSME Technology Test Bed (TTB) at MSFC. The OPAD system instrumentation consists of a broad-band, optical multiple-channel analyzer (OMA) and a narrow-band device called a polychrometer. The OMA is a high-resolution (1.5-2.0 Angstroms) "super-spectrometer" covering the near-ultraviolet to near-infrared waveband (2800-7400 Angstroms), providing two scans per second. The polychrometer consists of sixteen narrow-band radiometers: fourteen monitoring discrete wavelengths of health and condition monitoring elements and two dedicated to monitoring background emissions. All sixteen channels are capable of providing 500 samples per second. To date, the prototype OPAD system has been used during 43 SSME firings on the TTB, collecting well over 250 megabytes of plume spectral data.

One goal of OPAD data analysis is to determine how much of an element is present in the SSME plume. Currently these element concentrations are determined iteratively with the help of a computer code, SPECTRA4, developed at AEDC. Experience has shown that iteration with SPECTRA4 is an incredibly labor intensive task and not one to be performed by hand. What is really needed is the "inverse" of SPECTRA4 but the mathematical model for this inverse mapping is tenuous at best. However, the robustness of SPECTRA4 run in the "forward" direction means that accurate input/output mappings can be obtained. If the mappings were inverted (*i.e.*, *input* becomes *output* and *output* becomes *input*) then an "inverse" of SPECTRA4 would be at hand but the "model" would be specific to the data utilized and would in no way be general. Building a generalized model based upon known input/output mappings while ignoring the details of the governing physical model is possible through the use of a neural network.

The research investigation described in this report involves the development of a neural network to provide a generalized "inverse" of SPECTRA4. The objectives of the research were to design an appropriate neural network architecture, train the network, and then evaluate its performance.

NEURAL NETWORK MODEL OF SPECTRA4

The computer code SPECTRA4 generates spectra (intensity versus wavelength plots) based on concentrations of fourteen elements in the SSME plume. The goal of the current research project was to quickly and accurately predict these concentrations from a given spectrum using a neural network. To that end, an optimally connected neural network architecture was selected for study because of its fast training and subsequent execution speed. In contrast, a traditional neural network is usually fully-connected, requiring more training and slightly longer execution times. Also, by locating and removing all redundant connections, the resulting optimally connected network will be more robust and efficient.

SPECTRA4 generates spectra for wavelengths ranging from 3092 Å to 7000 Å for a given set of element concentrations. These concentrations are values ranging anywhere from 0.01 ppm to 100 ppm. Past experience with OPAD data analysis has revealed that the region of primary interest in any spectrum lies in the wavelength band of 3300 Å to 4330 Å. In order to discretize a spectrum, this region was broken into 42 subintervals of 25 Å each. The maximum intensity in each of these subintervals was then used as a neural network input, resulting in a network with 42 input neurons. The corresponding element concentrations which produced the spectrum in question were used as desired outputs, dictating a network with 14 output neurons. With the number of input and output neurons specified, the network was then trained for varying numbers of hidden neurons.

The design and training of an optimally connected neural network consists of two distinct phases. In the first phase, all connections between neurons in the network are fully established. Random numbers are assigned as interconnection weights. Then a genetic algorithm[1] optimizes the connections, de-linking all those found to be unnecessary. In the second phase, backpropagation of error is used to adjust the remaining weights. Backpropagation is a supervised mode of learning wherein the partial derivatives of the error with respect to the weights are used to adjust the weights until a minimum error is reached.[2] Once training is completed, the neural network with optimized connections and weights can be used to predict element concentrations given intensity versus wavelength information.

RESULTS

Once a neural network was trained, it was tested against randomly generated spectra. Typical results for a network with 60 hidden neurons and a training sample consisting of 50 data sets can be seen in Figure 1. The prediction error for some elements is very small while for others it is quite large. This suggests that the error criteria or the discretization of the spectra during training were not correct. However, it does appear that an optimally connected network is capable of modeling the "inverse" of SPECTRA4.

A study was also carried out to determine how the number of hidden neurons in a network affects the prediction error. Three networks with 30, 60 and 90 hidden neurons were considered. The total prediction error dependence upon the number of hidden neurons is presented in Figure 2. What is readily apparent is that blindly increasing the number of hidden neurons in a network does not guarantee increased prediction accuracy. This suggests that after a point the network is memorizing patterns rather that learning the relationships between them. An optimum number of neurons exists and must be determined.

SPECTRA4 SENSITIVITY STUDY

Another aspect of the current investigation was the sensitivity of the SPECTRA4 code. Since the concentrations of all the fourteen elements could vary between 0.01 ppm and 100 ppm, network training became extremely time-consuming. Also, the mapping space was found to be very large and noisy. In order to address these concerns, a sensitivity study of SPECTRA4 was initiated. To obtain a robust neural network, training data must be chosen from those regions of the mapping space for which the concentrations of elements are most sensitive.

Some preliminary results from the sensitivity study currently underway are available. They show that perturbing the concentrations of elements such as copper, sodium, lithium or magnesium do not cause any change in the values of the intensity peaks of all the subintervals in a discretized spectrum. Other elements, such as calcium, manganese, silver or aluminum cause a change in only a few subintervals. Elements such as iron, molybdenum, cobalt and nickel were found to be extremely sensitive as they cause a change in the intensity peaks of almost all intervals. These preliminary results are very interesting but more study is required to substantiate them.

CLOSING REMARKS

Optimally connected neural networks have been developed to grossly model the "inverse" of SPECTRA4. They will certainly aid in the analysis of OPAD data by eliminating some of the time-consuming iteration currently utilized. However, in order for the networks developed to be useful, the prediction error must be reduced for all elements and the robustness of the network demonstrated. These aspects are currently under study.

REFERENCES

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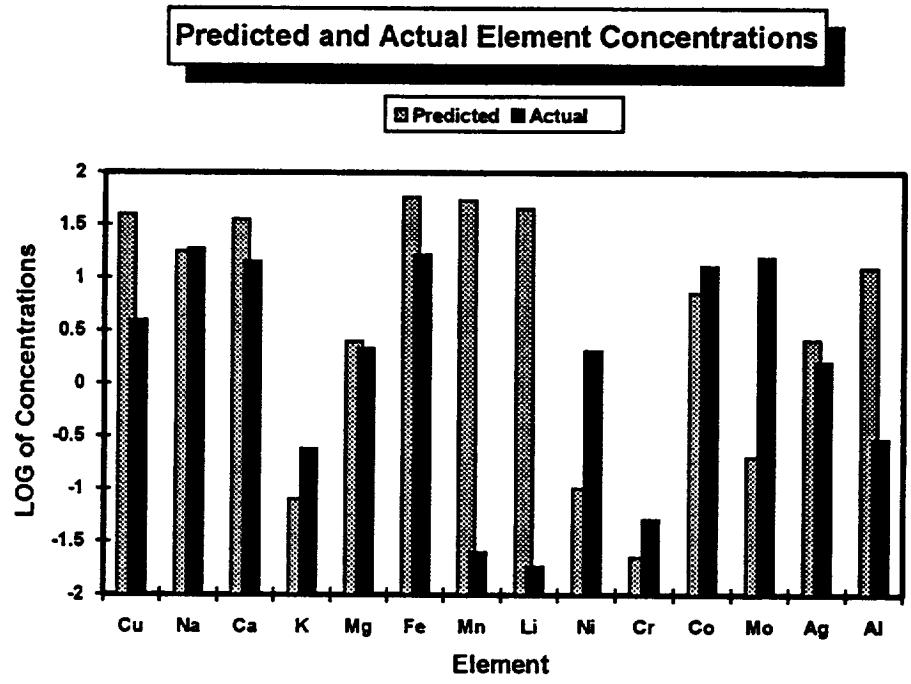

Figure 1. A comparison of predicted and actual element concentrations for a network with 60 hidden neurons

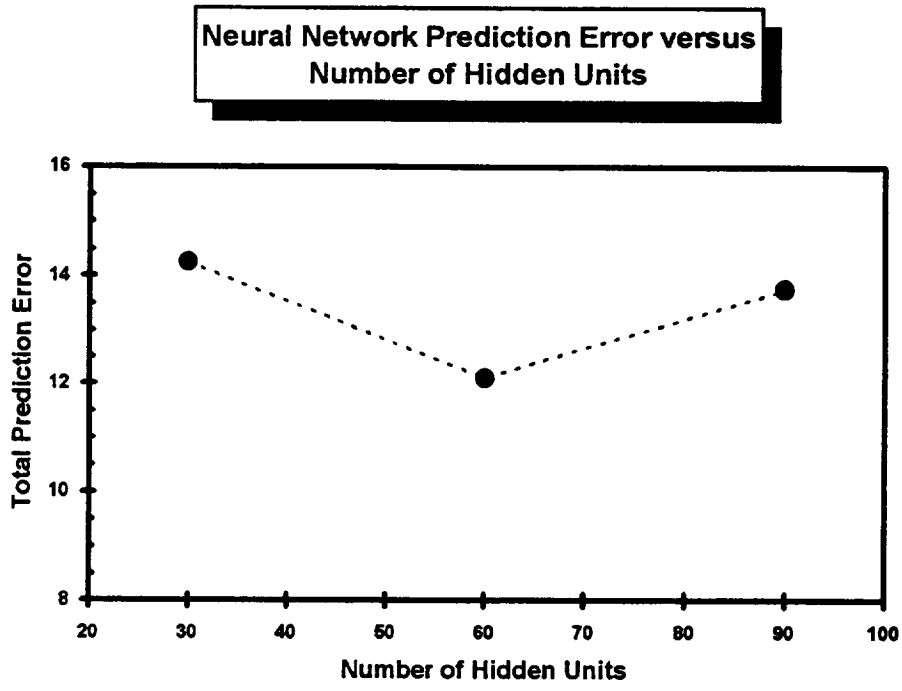

Figure 2. Relationship between prediction error and number of hidden neurons